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14. ABSTRACT

The investigators report on their findings, recent publication, and presentations in the areas of lenslet array imaging, wavefront encoding, and non-negative matrix factorization for material component (end-member) identification. Lenslet arrays enable a number of imaging modalities, including amplitude diversity, polarization diversity, wavelength diversity (multi-spectral data) and phase diversity. Each of these techniques extends traditional imaging by modifying the data acquisition to implicitly capture features that would otherwise be

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Final Report for Innovative Methods for High Resolution Imaging

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Current (2009) and prior results relating to pupil phase encoding were adapted to mitigate a frequency-agile pulsed laser attack against CCD-based cameras.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received   Paper

  TOTAL:

Number of Papers published in peer-reviewed journals:

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Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
2012/07/16 1(	12	R. Barnard, V. P. Pauca, T. C. Torgersen, R. J. Plemmons, S. Prasad, J. van der Gracht, J. Nagy, J. Chung, G. Behrmanne, S. Mathews, M. Mirotznik. High-Resolution Iris Image Reconstruction from Low-Resolution Imagery, Proceedings of SPIE Advanced Signal Processing Algorithms, Architectures, and Implementations XVI. 2006/08/13 00:00:00, . : ,
2012/07/16 1!	11	Qiang Zhang, Han Wang , Robert Plemmons, V. Paul Pauca. Spectral Unmixing using Nonnegative Tensor Factorization, Proceedings of the 2007 ACM Southeast Conference. 2007/03/23 00:00:00, . : ,
2012/07/16 1!	10	R. Barnard, B. Gray, V. Pauca, T. Torgersen, M. Mirotznik, J. van der Gracht, R. Plemmons, G. Berman, S. Mathews, S. Prasad. PERIODIC: State-of-the-Art Array Imaging Technology [Extended Abstract] , Proceedings of the 2007 Southeast Conference. 2007/03/23 00:00:00, . : ,
2012/07/16 1!	9	Robert Plemmons, Sudhakar Prasad, Scott Mathews, Mark Mirotznik, Ryan Barnard, Brian Gray, Paul Pauca, Todd Torgersen,, Joe van der Gracht, Greg Behrmann. PERIODIC: Integrated Computational Array Imaging Technology, OSA Conference on Computational Optical Sensing and Imaging. 2007/06/18 00:00:00, . : ,
2012/07/16 1₄	8	Kelly N. Smith, V. Paul Pauca, Arun Ross, Todd Torgersen, Michael C. King. Extended Evaluation of Simulated Wavefront Coding Technology in Iris Recognition, IEEE Conference on Biometrics: Theory, Applications, and Systems.. 2007/09/27 00:00:00, . : ,
2012/07/16 1₄	7	V. P. Pauca, D. Chen, J. van der Gracht, R. J. Plemmons, S. Prasad, T. C. Torgersen. Pupil Phase Encoding for Multi-Aperture Imaging, Proc. SPIE, Adsanced Signal Processing Algorithms, Architectures, and Implementations, XVIII. 2008/08/10 00:00:00, . : ,
2012/07/16 1₄	6	Lei Zhang, Todd Torgersen, Joseph van der Gracht, Paul Pauca. Pupil Phase Encoding for Mitigation of Laser-induced Saturation in Imaging Sensors, OSA Fall Optics & Photonics Congress 2009. 2009/10/11 00:00:00, . : ,

    TOTAL: **7**

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
2012/07/16 1₄	5	Robert J. Plemmons, Donghui Chen. Nonnegativity constraints in numerical analysis, Conference Proceedings of the Symposium on the Birth of Numerical Analysis. 2007/10/29 00:00:00, . : ,

    TOTAL: **1**

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received		Paper
2012/07/16 1₂	4	V. Paul Pauca, J. Piper, Robert J. Plemmons. Nonnegative Matrix Factorization for Spectral Data Analysis, Linear Algebra and its Applications, vol 416, pp. 29-47 (06 2006)
2012/07/16 1₂	3	Michael W. Berry, Murray Browne, Amy N. Langville , V. Paul Pauca, Robert J. Plemmons . Algorithms and Applications for Approximate Nonnegative Matrix Factorization, Computational Statistics & Data Analysis (01 2007)
2012/07/16 1₂	2	Qiang Zhang, Han Wang, Robert J. Plemmons, V. Paul Pauca. Tensor Methods for Hyperspectral Data Analysis: A Space Object Material Identification Study, Journal of the Optical Society of America A (01 2008)

    TOTAL: **3**

Number of Manuscripts:

Books

   TOTAL: **2**

Patents Submitted

Methods and Systems for Designing Electromagnetic Wave Filters and Electromagnetic Wave Filters Designed Using Same
(2008)

Patents Awarded

Awards

Graduate Students

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Todd C. Torgersen	0.11	
V. Paul Pauca	0.17	
Robert J. Plemmons	0.11	
FTE Equivalent:	**0.39**	
Total Number:	**3**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

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Names of Personnel receiving masters degrees

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Names of personnel receiving PHDs

NAME

Total Number:

Names of other research staff

NAME	PERCENT_SUPPORTED

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Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

See Attachment.

Technology Transfer

Report type: Final Report
Proposal Number: 48416MA
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Proposal Title: Innovative Methods for High Resolution Imaging and Feature Extraction
Report Period Begin Date: Aug. 1, 2005
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Authors :   T. C. Torgersen, V. P. Pauca, R. J. Plemmons
Institution :   Wake Forest University
                       300 S. Hawthorne Road
                       Winston-Salem, NC 27109

1 Abstract

The investigators report on their findings, recent publications and presentations in the areas of lenslet array imaging, wavefront encoding, and non-negative matrix factorization for material component (end-member) identification. Lenslet arrays enable a number of imaging modalities, including amplitude diversity, polarization diversity, wavelength diversity (multi-spectral data) and phase diversity. Each of these techniques extends traditional imaging by modifying the data acquisition to implicitly capture features that would otherwise be undetectable. Post-processing converts implicitly captured or encoded information to a form suitable for human or automated identification tasks.

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Current (2009) and prior results relating to pupil phase encoding were adapted to mitigate a frequency-agile pulsed laser attack against CCD-based cameras. The investigators performed a phase one SBIR with Agiltron Corp. to explore possible commercialization of pupil phase encoding technology. While this approach was not selected for phase two funding, the investigators showed that this approach is viable.

2 Publications

2.1 Publications in Peer-review Journals

1. V.P. Pauca, K. Smith, A. Ross, and J. van der Gracht. "Wavefront Coded Iris Biometric Systems," Encyclopedia of Biometrics, Li, Stan Z. (Ed.), Springer (ISBN: 978-0-387-73002-8), 2009.

2. P. Zhang, H. Wang, R.J. Plemmons, and V.P. Pauca. "Tensor Methods for Hyperspectral Analysis of Space Objects, A Material Identification Study," Journal of the Optical Society of America, A., Vol. 25, No. 12, pp. 3001-3012, 2008.

3. M.W. Berry, M. Browne, A.N. Langville, V.P. Pauca, and R.J. Plemmons. "Algorithms and Applications for Approximate Nonnegative Matrix Factorization," Computational Statistics & Data Analysis, Vol. 52, pp. 155-173, 2007.

4. V.P. Pauca, J. Piper, and R.J. Plemmons. "Nonnegative Matrix Factorization for Spectral Data Analysis," Linear Algebra and its Applications, vol. 416, pp. 29-47, 2006.

5. D. Chen and R. Plemmons, "Nonnegativity Constraints in Numerical Analysis," To appear in the Conference Proceedings of the Symposium on the Birth of Numerical Analysis, held Leuven Belgium, October 2007. World Scientific Press, A. Bultheel and R. Cools, Eds.

2.2   Non-Peer-Reviewed Conference Proceedings

6. J. van der Gracht, L. Zhang, T. Torgersen, and P. Pauca. "Pupil Phase Encoding for Mitigation of Laser-Induced Saturation in Imaging Sensors". Computational Optical Sensing and Imaging, OSA Technical Digest, San Jose, California, October 2009.

7. V.P. Pauca , D. Chen, J. van der Gracht, R.J. Plemmons, S. Prasad, and T.C. Torgersen. "Pupil Phase Encoding for Multi-Aperture Imaging," to appear in Proc. SPIE, Advanced Signal Processing Algorithms, Architectures, and Implementations XVIII, San Diego, CA, Aug. 2008.

8. K.N. Smith, V.P. Pauca, A. Ross, T. Torgersen, and M. C. King. "Extended Evaluation of Simulated Wavefront Coding Technology in Iris Recognition," IEEE Conference on Biometrics: Theory, Applications and Systems, September 27th to 29th, 2007.

9. (**invited short article**) R. Plemmons, S. Prasad, S. Mathews, M. Mirotznik, R. Barnard, B. Gray, V. Pauca, T. Torgersen, J. van der Gracht, and G. Behrmann. "PERIODIC: Integrated Computational Array Imaging Technology," OSA Technical Digest, Conference on Computational Optical Sensing and Imaging (COSI), Vancouver, 2007.

10. (extended abstract) R. Barnard, B. Gray, V. Pauca, T. Torgersen, M. Mirotznik, J. van der Gracht, R. Plemmons, G. Behrmann, S. Mathews, and S. Prasad. "PERIODIC: State-of-the-Art Array Imaging Technology," Proc. 2007 ACM Southeast Conference, pp. 544–546, Mar., 2007.

11. (extended abstract) Q. Zhang, H. Wang, R. Plemmons, and V. Pauca. "Spectral Unmixing Using Nonnegative Tensor Factorization," Proc. 2007 ACM Southeast Conference, pp. 531–532, Mar., 2007.

12. R. Barnard, V.P. Pauca, T.C. Torgersen, R.J. Plemmons, S. Prasad, J. van der Gracht, J. Nagy, J. Chung, G. Behrmann, S. Mathews, and M. Mirotznik. "High-Resolution Iris Image Reconstruction from Low-Resolution Imagery," Proc. SPIE, Advanced Signal Processing Algorithms, Architectures, and Implementations XVI, vol. 6313, pp. 1–13, San Diego, CA, Aug. 2006.

2.3 Book Chapter

13. M. Ng and R. Plemmons, "Blind Deconvolution and Structured Matrix Computations with Applications to Array Imaging", 46 Page Chapter in <u>Blind Image Deconvolution: Theory and Applications</u>, Edited by P. Campisi and K. Egiazarian, CRC Press, October 2007.

3 Presentations

- J. van der Gracht, Lei Zhang, V. P. Pauca, and T. Torgersen, "Pupil Phase Encoding for Mitigation of Laser-induced Saturation in Imaging Sensors", Computational Optical Sensing and Imaging (COSI), San Jose, CA, October 13-15, 2009.

- Technical Conference: October 13–15, 2009 R. Plemmons, (Invited), "Nonnegativity Constraints in Numerical Analysis", Symposium on : The Birth of Numerical Analysis, Leuven, Belgium, October 2007.

- R. Plemmons, (Invited), "Integrated Computational Lenslet Array Systems Applied to Bioimaging", Special Semester on Quantitative Biology Analyzed by Mathematical Methods, Linz, Austria, November 2007.

- R. Plemmons, (Invited), "Matrix and Tensor Methods for Space Situational Awareness", Colloquium at Louvain-la-Neuve University, Belgium, March 2008.

- R. Plemmons, (Invited), "Mathematical and Algorithms Challenges for Processing Hyperspectral Data", Croucher Advanced Study Institute on Mathematical and Algorithmic Challenges for Modeling and Analyzing Modern Data Sets, Hong Kong, China, April 2008.

- R. Plemmons, (Invited), "Nonnegativity Constraints for Linear Algebra in Scientific Computation", Householder Symposium, Berlin, Germany, May 2008.

- V.P. Pauca (Invited), "PERIODIC: Multi-Aperture Multi-Diversity Imaging," Community Academic Summit, Sponsored by the Defense Intelligence Agency, The National Geospatial Intelligence Agency, and the Disrupted Technologies Office, Williamsburg, VA, June, 2007.

- V.P. Pauca. (Invited), "Computational Imaging Systems: The Growing Intersection between Scientific Disciplines," Universidad Andina del Cusco, Cusco, Peru, July 2008.

- V.P. Pauca. "Pupil Phase Encoding for Multi-Aperture Imaging," SPIE Advanced Signal Processing Algorithms, Architectures, and Implementations XVIII, San Diego, CA, August 2008.

- T. Torgersen, "PERIODIC: Multi-Spectral Imaging for Rapid Evaluation of Thermal Injury", presented at the 2008 SIAM Annual Meeting, held July 7–11, San Diego, CA.

- T. Torgersen, "PERIODIC: Lenslet Array Imaging Technology", presented at the 6th International Congress for Industrial and Applied Mathematics, held July 16–20, 2007, Zurich, Switzerland.

- T. Torgersen, "PERIODIC: Digital Superresolution using Lenslet Array Technology" NATO ET051 Lab: Industry Day Briefings on Super-Resolution and Advanced Signal Processing, held September 26, 2007 at the US Army Night Vision Labs, Ft. Belvoir, VA.

4   Scientific Progress and Accomplishments

4.1   Summary of Results

We report on our scientific results in abstract summary form given below:

Pupil Phase Encoding

Digital super-resolution refers to computational techniques that exploit the generalized sampling theorem to extend image resolution beyond the pixel spacing of the detector, but not beyond the optical limit (Nyquist spatial frequency) of the lens. The approach to digital super-resolution taken by our multi-lenslet camera project is to solve a forward model which describes the effects of sub-pixel shifts, optical blur, and detector sampling as a product of matrix factors. The associated system matrix is often ill-conditioned, and convergence of iterative methods to solve for the high-resolution image may be slow.

We have investigated and published[1] the use of pupil phase encoding in a multi-lenslet camera system as a means to physically precondition and regularize the computational super-resolution problem. This is an integrated optical-digital approach that has been previously demonstrated with cubic type and pseudo-random phase elements. Traditional multi-frame phase diversity for imaging through atmospheric turbulence uses a known smooth phase perturbation to help recover a time series of point spread functions corresponding to random phase errors. In the context of a multi-lenslet camera system, a known pseudo-random or cubic phase error may be used to help recover an array of unknown point spread functions corresponding to manufacturing and focus variations among the lenslets.

The use of pupil phase encoding was also investigated as a possible means to mitigate a frequency agile laser attack on a CCD-based camera. Results are reported in [6]. An alternative approach based on a lenslet array design was also shown effective in simulation; however this technical approach also implied a significantly reduced field of view.

Biometric Identification

We investigated the use of a novel multi-lens imaging system in the context of biometric identification[2], and more specifically, for iris recognition. Multi-lenslet cameras offer a number of significant advantages over standard single-lens camera systems, including thin form-factor and wide angle of view. By using appropriate lenslet spacing relative

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[1]See references 7 in section 2.2.
[2]See reference 12 in section §2.2.

to the detector pixel pitch, the resulting ensemble of images implicitly contains subject information at higher spatial frequencies than those present in a single image. Additionally, a multi-lenslet approach enables the use of observational diversity, including phase, polarization, neutral density, and wavelength diversities. For example, post-processing multiple observations taken with differing neutral density filters yields an image having an extended dynamic range. Our research group has developed several multi-lens camera prototypes for the investigation of such diversities.

We presented techniques for computing a high-resolution reconstructed image from an ensemble of low-resolution images containing sub-pixel level displacements. The quality of a reconstructed image is measured by computing the Hamming distance between the Daugman4 iris code of a conventional reference iris image, and the iris code of a corresponding reconstructed image. We present numerical results concerning the effect of noise and defocus blur in the reconstruction process using simulated data and report preliminary work on the reconstruction of actual iris data obtained with our camera prototypes.

Non-Negative Matrix Factorization

In reference 3 (section §2.1 we discuss the development and use of low-rank approximate nonnegative matrix factorization (NMF) algorithms for feature extraction and identification in the fields of text mining and spectral data analysis. The evolution and convergence properties of hybrid methods based on both sparsity and smoothness constraints for the resulting nonnegative matrix factors are discussed. The interpretation of NMF outputs in specific contexts are provided along with opportunities for future work in the modification of NMF algorithms for large-scale and time-varying datasets.

Reference 5 (section 2.1 gives a survey of the development of algorithms for enforcing nonnegativity constraints in scientific computation. Special emphasis is placed on such constraints in least squares computations in numerical linear algebra and in nonlinear optimization. Techniques involving nonnegative low-rank matrix and tensor factorizations are also emphasized. Details are provided for some important classical and modern applications in science and engineering. For completeness, this report also includes an effort toward a literature survey of the various algorithms and applications of nonnegativity constraints in numerical analysis. Also see 4 in section §2.1 and reference 13 in section §2.3.

Tensor-Based Analysis for Material Identification from Hyperspectral Data

An important and well studied problem in hyperspectral image data applications is to identify materials present in the object or scene being imaged and to quantify their abundance in the mixture. Due to the increasing quantity of data usually encountered in hyperspectral datasets, effective data compression is also an important consideration. In references 2 of section §2.1 and reference 11 of section §2.2, we develop novel methods based on tensor analysis that focus on all three of these goals: material identification, material abundance estimation, and data compression. Test results are reported in all three perspectives.

4.2 Technical Approach

4.2.1 Pupil Phase Engineering

Pupil phase engineering (PPE), as it appeared in Prasad, et. al.[3] was developed as a constrained optimization problem to minimize sensitivity of the PSF to mis-focus, while maintaining a restorability metric above a minimal required threshold. A Fisher Information-based metric is ideal for measuring sensitivity of a property (e.g., the PSF) to a specific parameter, (e.g., mis-focus). Several restorability metrics are possible, however a metric based on the Strehl ratio proved to be a practical choice.

Pupil phase engineering is a more rational approach than ad-hoc choices of phase mask, since it brings numerical constrained optimization techniques to bear on a space of possible phase masks, arriving at an optimum solution with respect to a well defined metric.

For purposes of extended depth of focus in a biometric identification system, the Fisher information metric is minimized within a constrained set of phase masks ensuring adequate restorability. Minimizing the Fisher Information metric minimizes the sensitivity to focusing errors.

Let $\mathbf{u} = (v, w)$ denote an image plane coordinate vector, and let $\mathbf{r} = (x, y)$ denote a pupil plane coordinate vector. The PSF $h(\mathbf{u})$ in the image plane is given by:

$$h(\mathbf{u}) = |K(\mathbf{u})|^2, \tag{1}$$

where K is the following pupil integral involving the total pupil phase, $[\phi(\mathbf{r}) + \theta(\mathbf{r})]$:

$$K(\mathbf{u}) = \frac{1}{\lambda f \sqrt{A}} \int d\mathbf{r} P(\mathbf{r}) e^{i\left[\frac{2\pi}{\lambda f} \mathbf{u} \cdot \mathbf{r} + \phi(\mathbf{r}) + \theta(\mathbf{r})\right]}. \tag{2}$$

In this expression, $P(\mathbf{r})$ is the pupil function, equal to 1 inside the pupil and 0 outside for a clear pupil, $\mathbf{u} \cdot \mathbf{r}$ denotes the dot product of vectors $\mathbf{u}$ and $\mathbf{r}$, λ is the wavelength of illuminating light, f is the focal length, and A is the area of the pupil. For the purpose of extended depth of focus for biometric identification systems, the uncompensated pupil phase $\theta(\mathbf{r})$ is of form $\tau(x^2 + y^2)$.

Pupil phase engineering seeks a phase mask that allows the greatest possible insensitivity of the phase-encoded optical image to focus variation without unacceptably compromising the digital restorability of that image. A Fisher information-based metric measuring the sensitivity of the PSF to defocus may be defined as:

$$J_I(\tau) = \int h(\mathbf{u}, \tau) \left[\frac{\partial \ln h(\mathbf{u}, \tau)}{\partial \tau} \right]^2 d\mathbf{u} \tag{3}$$

$J_I(\tau)$ is a weighted average of the square (in log scale) of the rate of change of the point spread function with respect to the defocus parameter τ. If $J_I(\tau)$ is small, we expect the

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[3]S. Prasad, V.P. Pauca, R.J. Plemmons, T.C. Torgersen, and J. van der Gracht. Pupil-phase optimization for extended-focus aberration-corrected imaging systems. In *Proc. SPIE, Advanced Signal Processing Algorithms, Architectures, and Implementations XIV*, volume 5559, pages 335–345, Denver, CO, Aug. 2004. SPIE, SPIE.

PSF to change very little in a neighborhood of τ. A natural choice of optimization metric is given by the following integral of $[J_I(\tau)]^2$:

$$I(\tau_0) = \int_{-\tau_0}^{\tau_0} [J_I(\tau)]^2 \, d\tau, \tag{4}$$

where $(-\tau_0, \tau_0)$ denotes the (symmetric) range of defocus parameters of interest. The choice of τ_0 represents an important opportunity to integrate the mission requirements (required depth of focus) of the imaging task directly into the optimization step.

Minimizing $I(\tau_0)$ also admits phase masks for which the corresponding restoration problem is too ill-conditioned for practical use. A penalty, or barrier function is utilized to constrain the minimization of $I(\tau_0)$ to allow only phase masks whose corresponding restoration problems are sufficiently well conditioned.

4.2.2 Phase Encoding to Mitigate a Pulsed Laser Attack on a CCD Camera

The problem assumes a frequency-agile, pulsed laser capable adversary with intent on damaging or disabling a CCD surveillance camera. One possible counter-measure is to use phase encoding to spread the incoming beam to reduce the destructive energy delivered to any one point on the detector surface. Image reconstruction can (in theory) be then used to reconstruct an image suitable for the surveillance application of interest. A number of phase element design strategies have been considered including traditional cubic phase-mask, piece-wise linear, pseudo-random phase , and modified pupil phase engineering. It is straightforward to design a piece-wise linear phase element which takes an incoming point source and spreads it into 100 equally spaced points containing equal energy; this guarantees the required Strehl ratio of 0.01. Figure 1 (left) illustrates a point spread function using this approach. A trade-off exists between field of view and quality of restoration. If the field of view is appropriately masked, sub-images spread across sub-regions of the detector do not overlap, and may be treated as independently sampled images of the same scene. The generalized sampling theorem (see reference 11) can then be used to re-construct a high-quality image. A simulation study has shown this approach offers very good restoration in the presence of noise, but sacrifices field of view to attain the desired mitigation.
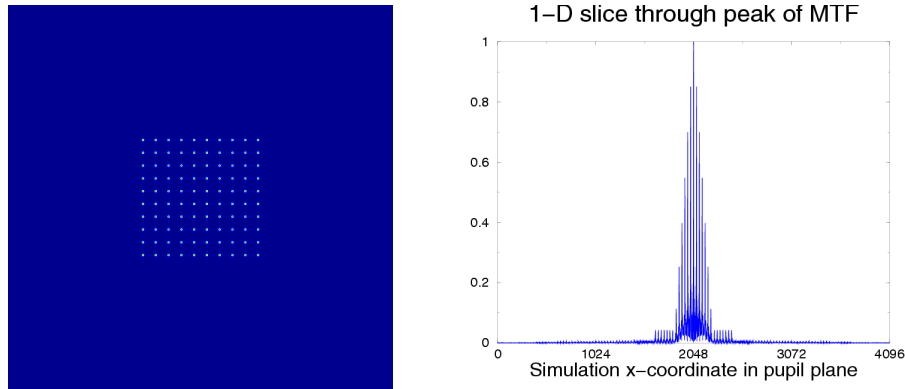

Figure 1: Point spread function (left) and corresponding MTF (right) for piece-wise linear phase perturbation

A summary of our results for this problem can be found in results [6].

7

4.2.3 Lenslet Array Imaging

Image formation using an array of lenslets focused on a single detector provides the raw data to reconstruct a high resolution image using the generalized sampling theorem. In this context, it is important to clarify the distinction between digital super-resolution and optical super-resolution. Digital super-resolution extends the image resolution beyond the sampling rate of the detector. Given multiple frames of the same scene, recorded with appropriate sub-pixel shifts among the frames, a well-understood theory shows that a high resolution image can be computed. Optical super-resolution extends the image resolution beyond the diffraction limit of the optical system. Recent information theoretic results show that optical super-resolution is not possible without additional sources of information, such as support constraints, non-negativity constraints, etc.

Lenslet Camera Image Formation Model

A low-resolution image, g_j formed by the jth lenslet is given by:

$$g_j = DH_j S_j f + \eta_j, \tag{5}$$

where,

- f is a target high-resolution representation for the object,

- S_j represents the translation of image f due to the relative position of lenslet j with respect to the object and the detector,

- H_j is a blurring operator associated with lenslet j,

- D is a decimation operator which represents the transformation from the target high resolution to the (low) resolution of the detector,

- g_j is the low-resolution image associated with lenslet j and,

- η_j describes a noise process associated with the jth image.

Inverse Problem Definition

For an n-lenslet camera we form a least-squares functional:

$$J(f) = \left\| \begin{bmatrix} DH_1 S_1 \\ DH_2 S_2 \\ \vdots \\ DH_n S_n \end{bmatrix} f - \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_n \end{bmatrix} \right\|_2^2 \tag{6}$$

whose minimum gives the desired estimate $\hat{f}$ for the high resolution image f. I.e.,

$$\hat{f} = \operatorname{argmin}_f \{J(f)\} \quad . \tag{7}$$

Inverse Problem Structure

When a pixel in f is shifted, it can only overlap a small number of neighbors. This implies there are only a small number of non-zero elements in each column of S_j. Conservation of light flux implies S_j must be column stochastic except at in columns corresponding to the boundary of the detector. H_j is circulant, and therefore efficient Fourier transforms can be used to evaluate the forward model. The down-sample operator D only integrates over a small number neighboring pixels in $H_j S_j f$. This implies there are only a small number of non-zero. elements in each row of D. The structure of the inverse problem implies that the forward model should be kept in factored form and that an iterative approach is most favorable. The current implementation described in [12] uses the well-known CGLS method.

Application to Biometric Identification

Figure (2) compares the performance of a single lenslet with our digital restoration using multiple lenslets under two distinct processing options. The horizontal axis represents the number of iterations used in the restoration method. The vertical axis represents the Hamming distance between the Daugman encodings of two iris image captures: a high-resolution reference image, and an image syntheized from data produced by a prototype camera. The dashed horizontal line at 0.32 on the vertical axis represents the threshold for successful biometric identification based on an iris match. The graph clearly show a favorable result when selecting a subset comprised of the best sub-images.
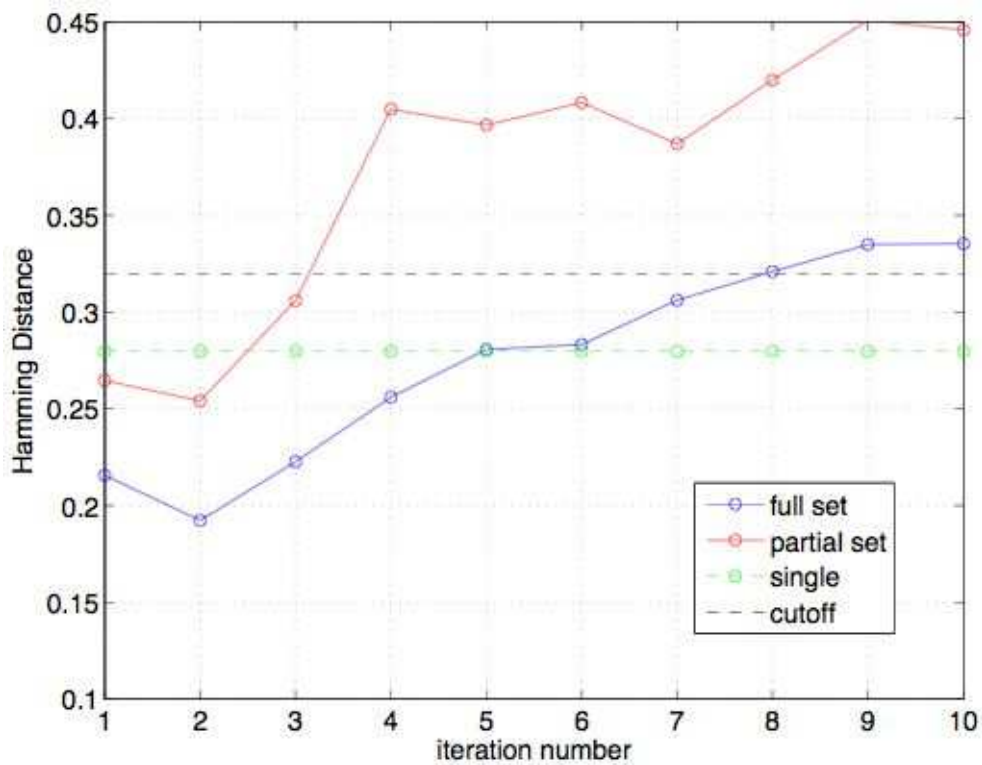

Figure 2: Comparison of single lenslet performance with multiple lenslet performance.

4.2.4 Non-negative Matrix Factorizaton and Non-negative Tensor Factorization

Three major objectives in processing hyperspectral image data of an object (target) are: data compression, spectral signature identification of constituent materials, and determination of their corresponding fractional abundances. In reference [11], the authors propose a novel approach to processing hyperspectral data using non-negative tensor factorization (NTF), which reduces a large tensor into three factor matrices; the Khatri-Rao product of these factors approximates the original tensor. This approach preserves physical characteristics of the data such as nonnegativity and can be used to satisfy all three major objectives. Test results are reported in reference [11] for space object identification.

Nonnegative Factorizations

In Nonnegative Matrix Factorization (NMF) and $m \times n$ (nonnegative) mixed data matrix X is approximately factored into a product of two nonnegative rank-k matrices, with k small compared to m and n, $X \approx WH$. This factorization has the advantage that W and H can provide a physically realizable representation of the mixed data. NMF is widely used in a variety of applications, including air quality control, image and spectral data processing, text mining, chemometric analysis, neural learning processes, sound recognition, remote sensing, and object characterization. Nonnegative Tensor Factorization (NTF) is a natural extension of NMF to higher dimensional data. In NTF, high-dimensional data, such as hyperspectral or other image cubes is approximated by a sum of rank one nonnegative tensors. The algorithms given below combine features of both NMF and NTF methods.

Definition 1: We define a non-negative rank-k decomposition of the tensor τ as:

$$\min_{x^{(i)}, y^{(i)}, z^{(i)}} \left\| \tau - \sum_{i=1}^{k} x^{(i)} \circ y^{(i)} \circ z^{(i)} \right\|_F^2$$

subject to

$$x^{(i)} \geq 0, \ y^{(i)} \geq 0, \ z^{(i)} \geq 0$$

where $\tau \in \mathcal{R}^{D_1 \times D_2 \times D_3}, x^{(i)} \in \mathcal{R}^{D_1}, \ y^{(i)} \in \mathcal{R}^{D_2}, \ \text{and} \ z^{(i)} \in \mathcal{R}^{D_3}$.

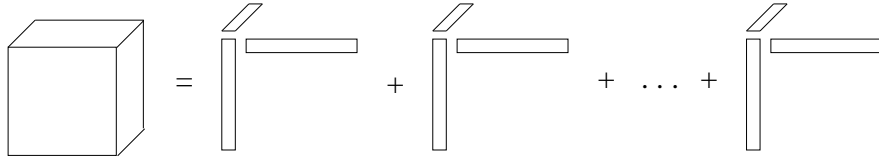A graphical depiction of the decomposition problem is given in figure 3 below.

Figure 3:

NTF Algorithm

- Group x_i's, y_i's, and z_i's as columns in $X \in \mathcal{R}_+^{D_1 \times k}$, $Y \in \mathcal{R}_+^{D_2 \times k}$, and $Z \in \mathcal{R}_+^{D_3 \times k}$ respectively.

- Initialize X and Y by Nonnegative Matrix Factorization of the mean slice,

$$\min_{X,Y} \left|\left|\ A - XY^T\ \right|\right|_F^2$$

  where A is the mean of τ across the third dimension.

- Iterative Tri-Alternating Minimization

  1. Fix τ, X, Y, and fit Z by solving a NMF problem using a projected gradient descent algorithm.
  $$\min_{Z} \left|\left|\ T_z - C_z Z^T\ \right|\right|_F^2$$
  where $C_z = X \odot Y \in \mathcal{R}^{D_1 D_2 \times k}$, T_z is the unfolding tensor across the third dimension, and $\odot$ represents the Khatri-Rao product.
  2. Fix τ, X, Z, and fit Y as above.
  3. Fix τ, Y, Z, and fit Z as above.

The algorithm given above has been shown in simulation to effectively identify the fractional abundances present in a computer-generated data model of the Hubble Space Telescope. A data volume of $177 \times 193 \times 100$ was successfully processed.

5   Technology Transfer

5.1   Mitigating Pulsed Laser Attack on CCD-based Cameras

The WFU imaging group was contacted in April 2008 by Agiltron Corporation to cooperatively develop an SBIR proposal entitled "Utilizing Computational Imaging for Laser Intensity Reduction at CCD Focal Planes"[4]. This collaboration facilitates technology transfer and commercialization of Pupil Phase Engineering (PPE) methods developed by the WFU imaging group and Dr. Sudhakar Prasad of the University of New Mexico. The collaborators wish to thank the Army Research Office (ARO) for their generous support during the development of PPE methods.

Todd Torgersen and Joe van der Gracht of Holospex, Inc. assisted Agiltron with the technical portion of the phase I proposal, and served as consultants during the performance period. Agiltron and WFU were invited to submit a phase II proposal, and submitted one in September 2009. While this proposal was not selected for phase two funding, the investigators showed that their approach is viable.

The problem of interest is to apply computational imaging[5] to mitigate the effect of a pulse laser attack on a CCD based camera. The basic approach is to choose a pupil-phase

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[4]See topic A08-064, URL: http://www.armysbir.com/awards/sbir_08ph.1_company.htm
[5]Optical design combined with digital post-processing.

perturbation which will spread out the incoming energy such that the PSF peak energy impacting any single detector pixel is reduced by a factor of 100. The assumption of a frequency-agile, pulsed laser capable adversary excludes solutions based on simple band-pass filtering, electro-mechanical shutters, or even digitally controlled transmissive LCD elements.

Several pupil phase encoding elements were investigated, including a traditional cubic phase pertubation, a piece-wise linear element relating to sub-aperture techniques, and a pseudo-random based phase pertubation. These approaches are discussed in [6].

5.2   Rapid Assessment of Thermal Injury

The co-investigators are currently collaborating with Dr. J. Molner at the Wake Forest University School of Medicine to adapt multi-spectral lenslet array imaging techniques to the problem of rapid assessment of thermal injuries. Unfortunately, thermal injuries are often progressively widening (or deepening). Injured (but still living) tissue near "ground zero" may receive reduced blood flow in the days following the injury, leading to an expanding area of non-viable tissue. Traditional treatments may require hospitalization, heavy medication, and very low patient mobility for several days before the correct surgical (e.g., skin graft) boundaries become apparent. The goal of this study is to evaluate several possible technologies which may predict viable and non-viable regions at the earliest possible time. Multi-spectral imaging allows us (in theory) to map regions of reduced (or increased) blood flow based on localized oxygenation levels. The spectral response of hemoglobin and oxy-hemoglobin differ markedly at several wavelengths, thus the spectral response is well correlated to percentage of blood oxygenation. The challenges posed by this work include 1) highly accurate calibration of all aspects of data acquisition, 2) the effect of skin pigmentation, and 3) integration of accurate scattering models. The results of this investigation are found in "Assessment of hemodynamic changes of pig skin in the post-burn period using a multi-spectral multi-aperture camera", WFU technical report.